EEG SIGNAL CLASSIFICATION

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Abstract – **The article describes the classification of simple movements using a system based on Hidden Markov Models (HMM). Brisk extensions and flexions of the index finger, and movements of the proximal arm (shoulder) and distal arm (finger) were classified using scalp EEG signals. The aim of our study was to develop a system for the classification of movements which show EEG changes at identical scalp electrodes of one hemisphere. The classification of EEG patterns related to movements of one hand is difficult because the disentanglement of movements can only rely on the temporal evolution of EEG changes at one recording site. A large variability of EEG waveforms requires the use of the context information.**

The classification procedure was optimized in all parts to increase the recognition score and it was extensively tested on a set of EEG data. The average classification score was 80%, std. deviation 9% for the classification of distal and proximal movements.

The classification of extension/flexion reached even better results (due to more accurate localization of the signal source on the scalp). The classification of movement-related EEG data based on HMM yielded higher recognition scores than previously reported classification scores based on artificial neural networks (NaN).

Keywords – Spectral analysis, Hidden Markov models, HTK, EEG classification, EEG synchronization

I. INTRODUCTION

The aim of our work was to develop, analyze, optimize and verify a HMM system for the classification of characteristic shapes of EEG signals. The key requirement built into the classification system was to use changes in signal parameters rather than information about the electrode position on the scalp. Successful classification of movement-related EEG signals is a pre-requisite for on-line classification of movement-related EEG data which can be utilized in driving of external devices, e.g. the Brain-Computer Interface (see [1]).

The classification of EEG signals shares similar characteristics with speech classification – e.g. the use of the context information contained in the signal. Due to smaller signal variability, speech classification is more straightforward than the EEG classification. EEG signals also show large inter-individual variability precluding extrapolation of EEG classification from one subjects to the whole sample. Here we applied the classification methods originally developed in the recognition of speech patterns to the EEG signals and thus we were able to improve the individual recognition scores.

The first step in the classification of movement-related EEG data was to choose a suitable classification paradigma. We have tried to fulfill the following conditions:

1. the ability to use context for recognition,
2. the possibility of finding out “what does the system learn”,
3. the reduction of the number of arithmetic operations.

Condition 1 is essential for reaching a satisfactory recognition score. The EEG signals display a context information and previous study pointed to the importance of the context information in EEG classification (see [2]). Condition 2 highly facilitates debugging and testing of the system. The third condition is of technological and practical importance.

These conditions seems to be satisfied using the approach based on HMM rather than NaN because of the following reasons:

- it is difficult to obtain mapping using NaN,
- NaN require substantially more numeric operations during the learning phase than HMM,
- HMM allow to model the shapes of EEG signals,
- HMM allow a straightforward use of the context information.

The above characteristics of HMM give a reliable recognition of speech patterns [3],[4]. The HMM has been applied recently to recognition of EEG patterns related to left and right hand movements [5]. In contrast to the study [5], HMM in our study was implemented to classify movements showing EEG changes at identical scalp electrodes of one hemisphere. Therefore the classification of EEG patterns related to movements of one hand is more difficult compared to classification of movements related to two hands (left vs. right) because the disentanglement of movements can only rely on the temporal evolution of EEG changes at one recording site (or in the worst case - at one electrode only).

II. PROPERTIES OF EEG SIGNAL

Prior to the classification system is designed, the analysis of EEG signal characteristics has to be performed.

A. THE SELECTION OF ELECTRODE

Since EEG changes in both, time and space, the selection of appropriate EEG electrode representing movement is a crucial point for a successful classification of movements.

Since movements are controlled primarily by the contralateral sensorimotor cortex, the suitable electrode are those overlying the contralateral sensorimotor hand area (electrode C3).

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Abstract

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We have tested various electrodes and came to the conclusion, as expected, that the selection of electrode has a serious impact on the recognition score (see [6] for more details).

B. Spectral analysis

The major differences in EEG data between two types of movements can be observed from the time course of spectral parameters. The changes of spectrum accompanying movement are localized to the 10-23 Hz band. The accurate selection of band is an individual task. To minimize the faulty choice, initially a broad band (0-40 Hz) band with removed DC component for classification ("baseband") was used.

One can see two characteristic phenomena in the spectrogram around the time of a movement (see [7]):

synchronization : post-movement rise of spectral power. Synchronization is usually greater in proximal than in distal movements (see Fig. 2 and Fig. 1 – compare the curve p with curve d in the interval III).

desynchronization : decrease of power around the time of movement onset (see interval II – Fig. 1). Desynchronization is stronger in distal than in proximal movements.

Figure 1 illustrates an example of the time development of the average magnitude spectrum of both movements for one subject and electrode. The spectrum is normalized, that is the amplitude of each spectral line is based to the average magnitude of the same spectral line computed from the segments 1 - 15. To be more precise: let $X_k^p[i]$ is the spectral line from segment k (frequency i Hz) of motion p, then the appropriate value Y_k^p (depicted on the figure) is computed as

$$Y_k^p = \frac{\sum_{i=10}^{23} X_k^p[i]}{\frac{1}{15}\sum_{i=10}^{23}\sum_{j=1}^{15} X_j^p[i]}. \tag{1}$$

C. Selection of parametrization

The results of spectral analysis revealed that the use of linear spectrum is the most appropriate for HMM. Other parameters (e.g. cepstral coefficients or log-spectra) were also tested but these parameters were found to be less suitable for the EEG classification.

The present system uses as the input parameters the spectral lines of linear magnitude spectrum taken from band 1 - 40 Hz without normalization used for Fig. 1. The reason is that in the real applications it is not possible to recognize the resting periods between subsequent movements. Our tests also showed that a successful classification is not sensitive to the selection of particular spectral lines. It is only important to detect a clear synchronization and desynchronization in the selected bands. Higher frequency bands (above 50 Hz) are not used since these bands showed poor signal-to-noise ratio.

III. Parameters of HMM Based Models

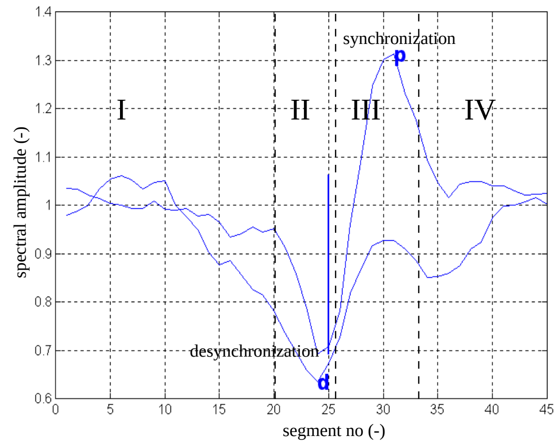

Figure 1: Person 4, electrode 25, 10-23 Hz band. Horizontal line marks the moment of movement, desynchronization can be found round the movement, after the movement is obvious synchronization. The shape of proximal movement is "p", "d" is for distal one.

Since we classify two types of movements, two models should be used – one for the distal, and the other for the proximal movement. The EEG epochs corresponding to the realizations of movements are stored in separate files. This way is very similar to isolated words recognition problem. The proposed grammar of the system is $distal$ **or** $proximal$.

During the selection of the type of model, the time courses of EEG synchronization and desynchronization shown in Fig. 1 are relevant. The whole time evolution of the EEG spectrum can be divided into four phases as depicted in Fig. 1. Phase I and IV are the resting periods preceding and following a movement, respectively. Phase II is the desynchronization, III is the synchronization. Phases follow in the order I – II – III – IV, none of them can be skipped. Also this situation is very similar to speech recognition. As the best it appears to use the model of type "left-right without skips", 4 emitting states. It is supposed that each state 1–4 is trained to the average magnitude spectrum corresponding to phases I – IV.

In Fig. 3 the mean values of output distributions of the model states are shown. In states 2 and 3, a decreasing and subsequent increasing of spectral power (in the band 10-20 Hz) is evident.

The results showed also a large variability of individual spectral changes. The standard deviation of spectral lines is typically higher than their mean values. The average shapes of spectral changes depicted in Figs. 1 and 3 fit to the prevailing number of subjects ([6]).

IV. Details of Parametrization

In the phase of parametrization, the following parameters should be optimized: segmentation length, segmentation step, weighting of signal segment by an appropriate weighting function, the type of stochastic distribution of spectral lines. For

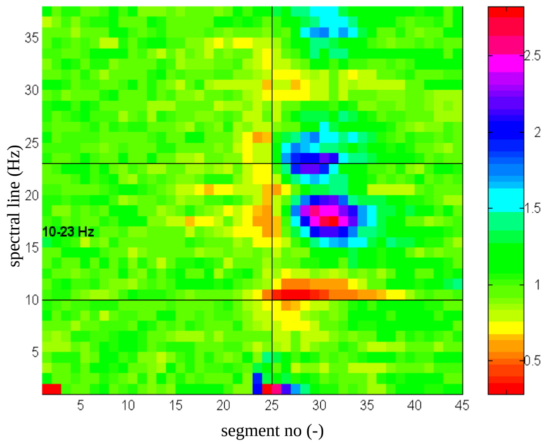

Figure 2: Person 4, electrode 25, the time development of the magnitude spectrum. Depicted is the baseband. Horizontal line marks the time of movement, you can see desynchronization round the movement and synchronization after the movement. Horizontal lines emphasize 10-23Hz band.

each parameter, an optimal value which maximizes the classification score can be found. Now we will give an overview of these optimal parameters.

A. Signal segmentation

For a reliable EEG signal classification, it is necessary to find a compromise between the frequency and time resolution. The unsuitable selection of one of these parameters results in decreasing of the recognition score.

Available frequency and time resolution is determined by the segment length. Time resolution is necessary for the proper recognizing of states I – IV. Low frequency resolution decreases the recognition score because individual states are not recognized due to big spectral bias. The optimal segment length was found to be 1 s that corresponds to 512 samples for sampling frequency $f_s = 500$ Hz.

The spectral window is shifted through the EEG epochs in short intervals, thus with a large temporal overlap. In our study, the overlap of 800 ms (400 samples) gave the best recognition scores. Thus, the resulting frequency resolution is 1 Hz and the time resolution (window shift) is 200 ms. These results correspond to the results given in [7].

B. Weighting of spectrum

The influence of spectral leakage on the recognition score was found to be negligible (see[6]).

C. Spectral lines distribution

The proposed system works with the signals with normally distributed parameters. However, the amplitudes of spectral lines usually show a logarithmic-normal distribution. Using the χ^2 test, we tested the distribution of our spectral parameters. The results showed (see [6]), that the distribution of magnitudes of spectral lines can be well approximated by both the normal and logarithmic-normal distributions. We performed several experiments with the conversion of the spectral parameters from the logarithmic-normal distribution to the normal distribution. However, the results were equivalent for both types of distributions.

D. Model parameters estimation

The influence of the number of Baum-Welch re-estimations [8] on the classification score was also studied. The optimal number of iterations is strongly influenced by the variability of EEG data and, of course, by the number of data. The best results for the set of data used (see section ”Experiments and results”) were achieved with ten Baum-Welch iterations. A smaller number of iterations have not trained the models sufficiently, and a large number of iterations (greater than 10) resulted in “over-trained” models.

E. The process of evaluating the results

Classification is a complicated statistic process. The results of experiments are at most influenced by

1. signal parameters and used parametrization,
2. the division of realizations between testing and training set.

The testing and training sets represent disjoint classes. Therefore, it is essential to repeat each experiment with different partitioning of realizations between both sets and to evaluate the recognition scores statistically.

A system for automatic partitioning the realizations between training and testing sets was implemented. Every experiment was repeated 10-times and the appropriate statistical criteria were evaluated.

V. Experiments and results

Parameters of the system were optimized and the whole system was extensively tested in numerous experiments. Here we present the typical parameters of the system and the results of classification (more details can be found in [6]).

Parameterization: segment of 512 samples length, overlap 400 samples, data recorded from electrode C3, 7 experimental persons, every vector contains 40 parameters (4 – 44Hz, step 1 Hz), 1 stream, none differential parameters.

Training: models trained on one half of data from a relevant subject, the second half was used for evaluating the recognition score. Used left-right model without skips, four emitting states. 10 steps of initialization, 10 steps of Baum-Welch reestimation.

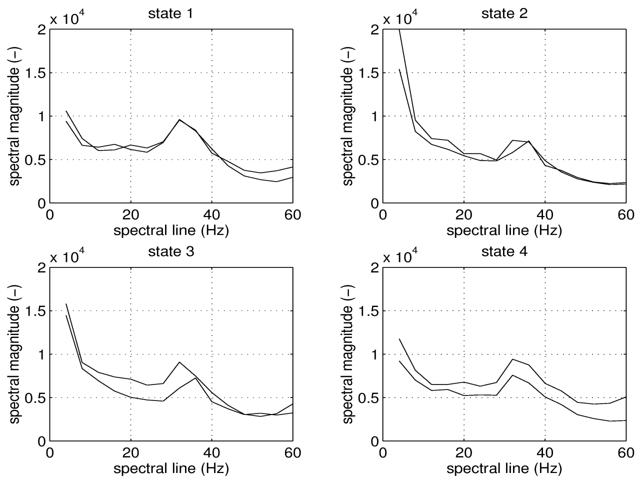

Figure 3: Means of state output distribution of model. You can compare them with the corresponding phases on Fig. 1 – state 1 corresponds with phase I, state 2 with phase II, 3 with III a 4 with IV.

Classification: classification was done by means of Viterbi algorithm. Each experiment was ten times repeated with its own division of realization between training and testing sets, the resultant classification score was the average of the scores from each repetition. Also the standard deviations for classification scores were evaluated.

Results: the average classification score for distal movement (extension-flexion of right index figner) - 80%, for proximal movement (right shoulder) - 76%. In both cases the standard deviations of recognition score are about 9%.

VI. Conclusions

The classification of movement-related EEG data based on the HMM is a feasible alternative to NaN. The problem of an optimal electrode used for classification is a problem common to the HMM and NaN approaches. Another problem is the large intra- and inter-individual variability of EEG data. Therefore, the classification of models cannot be straightforwardly generalized to the whole population of subjects. The suggested system is able to recognize only the movement-related EEG data which were used for training. The low capacity of the EEG models is the reason that no generalization of models can be achieved. In this point the used approach differs from the classification of speech patterns for which a “speaker independent classification” is possible. The using of the EEG classification models for more different movements and for more than one subject is a task for the future. The next study will be performed on a larger database of EEG signals and for more different types of movements.

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